Midterm project
Dog Emotions

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I. Introduction

Our algorithm analyzes images of dogs and attempts to ascertain their emotions. The dataset has four classes: Happy, Sad, Relaxed, and Angry. Furthermore, we downsized each image to 224x224 pixels and applied random flipping, rotation, and color jittering. The dataset comprises a total of 4000 images, and it is entirely balanced. We partitioned the dataset in a 70:20:10 ratio for training, testing, and validation, accordingly. We employed ResNet and VGG models with and without transfer learning across 20 epochs. We adjusted the model and altered the output layer to accommodate four classes. Utilizing SGD and Adam as optimizers, we concentrated on accuracy, loss, and F1 scores. Furthermore, given that there were only four classes, the accuracy for each class is also taken into account.

II. Model Results

Model	Pretrained	Freeze	Optimizer	Train Loss	Val Loss	Val F1	Test Acc	"Angry"	"Happy"	"Relaxed"	"Sad"
resnet	no	-	sgd	1.1552	1.0997	0.535	0.5498	24.88	64.18	74.63	56.22
resnet	no	-	adam	0.7709	0.8433	0.6925	0.6642	78.11	52.74	68.16	66.67
resnet	yes	no	sgd	0.1467	0.4964	0.86	0.8371	82.09	87.56	87.56	77.61
resnet	yes	no	adam	0.129	0.7212	0.84	0.806	82.09	78.11	79.1	83.03
vgg	no	-	sgd	1.3483	1.3601	0.3175	0.2935	12.44	1	6.97	97.01
vgg	no	-	adam	1.3866	1.3863	0.25	0.25	0	0	0	100
vgg	yes	no	sgd	0.0767	0.6216	0.8725	0.842	88.06	88.56	79.6	80.6
vgg	yes	no	adam	0.1868	0.7355	0.83	0.7973	76.12	90.05	92.04	60.7
resnet	yes	yes	sgd	0.9271	0.8405	0.71	0.6182	40.8	70.65	75.12	60.7
resnet	yes	yes	adam	0.4987	0.7988	0.7175	0.6219	62.65	65.17	65.67	55.22
vgg	yes	yes	sgd	0.2506	0.9339	0.75	0.6978	73.63	56.72	69.15	79.62
vgg	yes	yes	adam	0.2477	0.7459	0.7575	0.7251	76.62	60.7	77.11	75.62

TABLE I: Comparison of models, training settings, and performance metrics.

III. Deep Analysis

Overall, the models did not perform as well as anticipated in our experiments. Due to the high complexity of the models and the limited size of our dataset—which contains only 4 classes—they tend to overfit after a few epochs. This means they memorize the training data in detail, which limits their ability to generalize. This issue is especially noticeable in the VGG16 model.

ResNet18

Untrained Models:

- **SGD:** Struggles to capture features specific to each class, resulting in low F1 scores (Train: 0.535, Val: 0.5498). Performs slightly better on classes 2 and 3.
- **Adam:** Demonstrates better generalization with higher F1 scores (Train: 0.6925, Val: 0.6642). Performs particularly well on class 0 (78.11%) but shows signs of underfitting on class 1.

Pretrained with Fine-Tuning:

- **SGD:** Delivers the best overall results, with balanced performance across all classes (82.09%–87.56%). Shows strong learning capabilities for all classes, though slightly less effective on class 3.
- **Adam:** CCompetitive results, but shows signs of overfitting (Train Loss: 0.129, Val Loss: 0.7212). Performs very well on class 3 (83.03%) but lags slightly on class 1. Training and validation loss curves indicate a widening gap, with validation loss increasing over time.

Pretrained with Frozen Layers:

- Both **SGD** and **Adam** struggle to adapt, indicating underfitting (F1 ¡ 0.72). Performance is especially poor on class 0, while classes 1 and 2 maintain moderate results.

VGG16

Untrained Models:

- **SGD:** Shows significant underfitting (F1: 0.3175, Test Accuracy: 29.35%), learning almost exclusively from class 3 (97.01
- **Adam:** Fails to generalize entirely (Test Accuracy: 25%), indicating that this optimizer is ineffective for training VGG16 from scratch. This is evident from loss graphs that remain almost flat.

Pretrained with Fine-Tuning:

- **SGD:** Achieves the highest performance, with balanced F1 scores (Train: 0.8725, Val: 0.842) and consistent class accuracies (88.06%–80.6%), performing especially well on classes 0 and 1.
- **Adam:** Performs reasonably well overall but struggles notably with class 3 (60.7%), with slightly lower metrics than SGD.

Pretrained with Frozen Layers:

- Outperforms ResNet18 under the same configuration, reaching around 0.75 F1 scores and steady performance across most classes. However, SGD struggles with class 1 in particular.

IV. Graphs

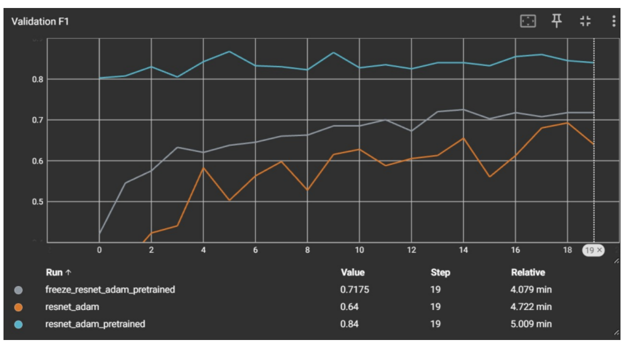

Fig. 1: Validation F1 ResNet with Adam

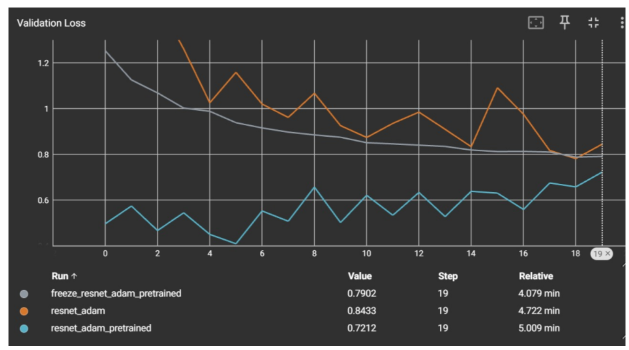

Fig. 2: Validation Loss ResNet with Adam

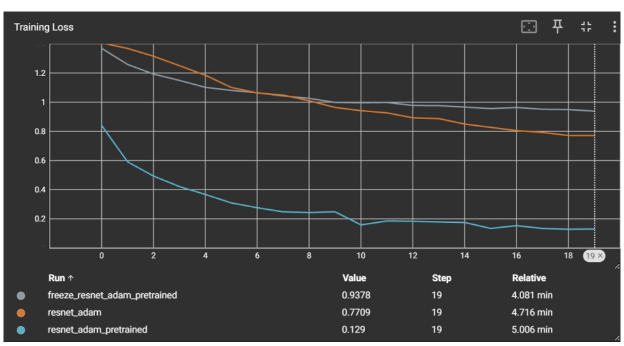

Fig. 3: Training Loss ResNet with Adam

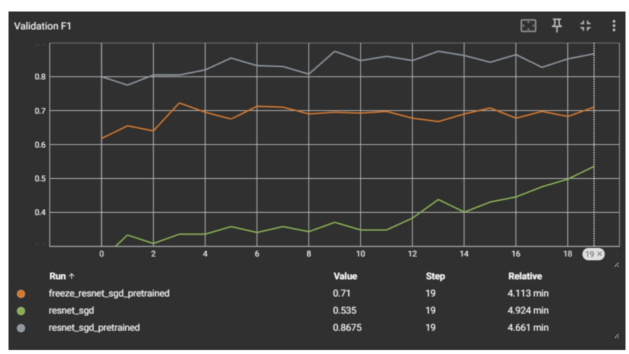

Fig. 4: Validation F1 ResNet with SGD

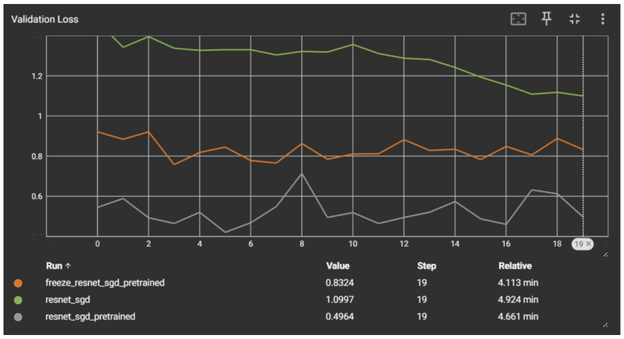

Fig. 5: Validation Loss ResNet with SGD

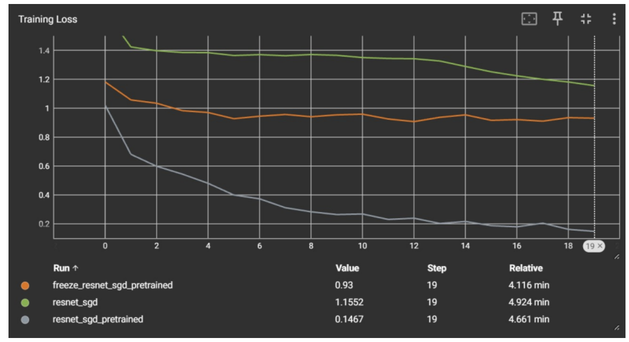

Fig. 6: Training Loss ResNet with SGD

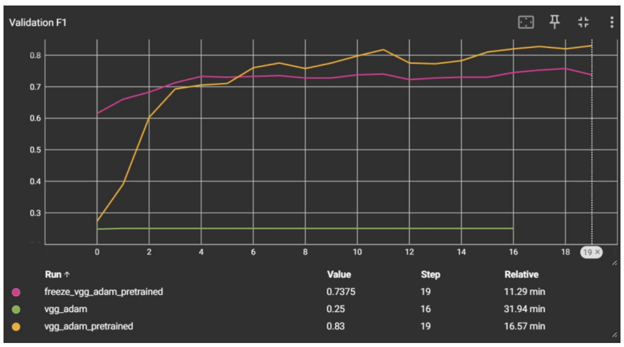

Fig. 7: Validation F1 VGG with Adam

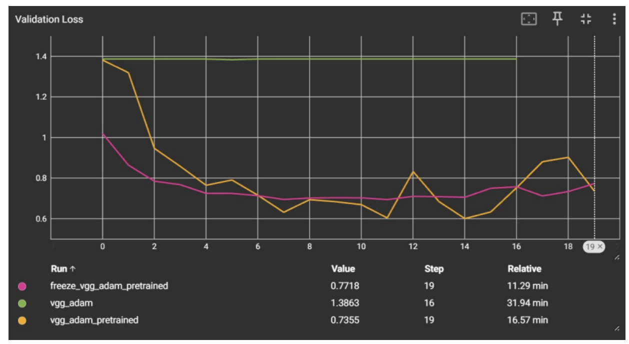

Fig. 8: Validation Loss VGG with Adam

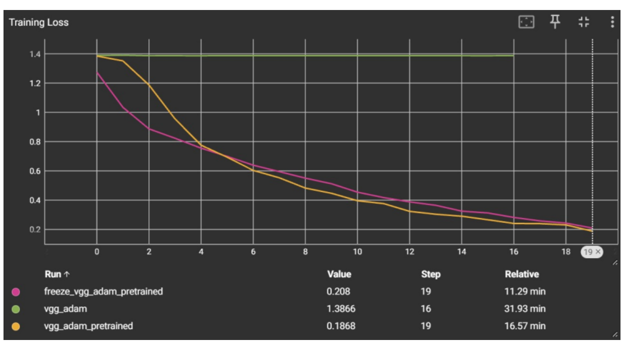

Fig. 9: Training Loss VGG with Adam

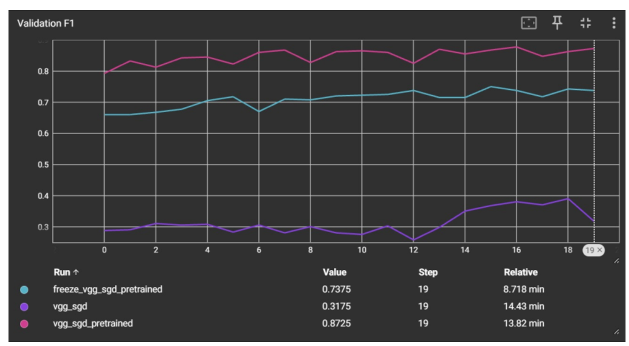

Fig. 10: Validation F1 VGG with SGD

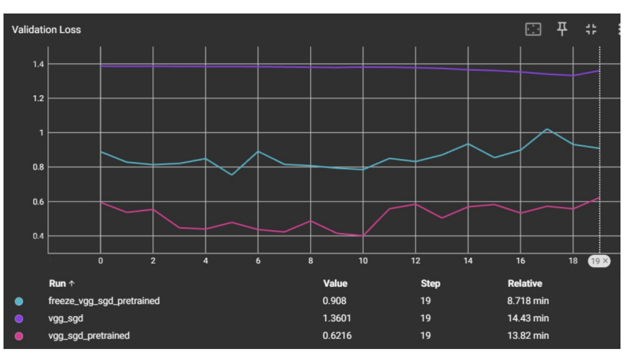

Fig. 11: Validation Loss VGG with SGD

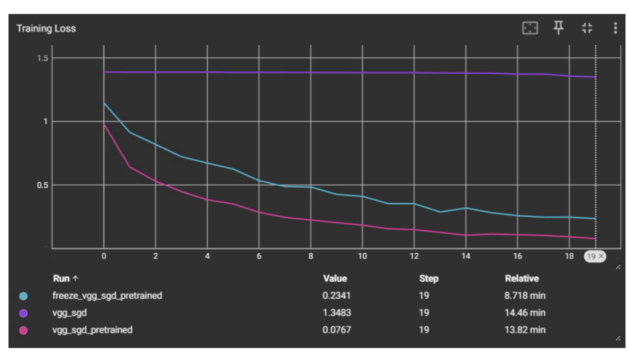

Fig. 12: Training Loss VGG with SGD